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Clustering-based location in wireless networks

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A B S T R A C T

In this paper, we propose a three-phase methodology (measurement, calibration and estimation) for locating mobile stations (MS) in an indoor environment using wireless technology. Our solution is a fingerprint-based positioning system that overcomes the problem of the relative effect of doors and walls on signal strength and is independent of network device manufacturers. In the measurement phase, our system collects received signal strength indicator (RSSI) measurements from multiple access points. In the calibration phase, our system utilizes these measurements in a normalization process to create a radio map, a database of RSS patterns. Unlike traditional radio map-based methods, our methodology normalizes RSS measurements collected at different locations (on a floor) and uses artificial neural network models (ANNs) to group them into clusters. In the third phase, we use data mining techniques (clustering) to optimize location results. Experimental results demonstrate the accuracy of the proposed method. From these results it is clear that the system is highly likely to be able to locate a MS in a room or nearby room.

1. Introduction

The use of wireless technology has expanded over recent years. Universities, private companies, as well as stations and airports all provide wireless communication facilities. This type of networks can be implemented using what are known as access point devices that provide total connectivity over a surface and connection to Internet. Several such devices are sometimes necessary to cover an office, a university or an airport.

One of the services to be implemented on these networks is user location on the premises. Through location and the visualization of a plan of the coverage area, users can navigate the premises as they would do using GPS navigation in an outdoor environment. Additionally, a network manager would be able to pinpoint users in such environments and interact with them through their positioning. Indoor positioning technology can also complement mobile–telephone-based GPS user positioning to determine the users exact location indoors.

In another context, location tracking is an essential feature for enterprises building business-critical wireless networks. If information technology (IT) staff can identify and track the location of wireless clients and highly mobile assets, they can improve the accuracy of WLAN planning and deployment, optimize ongoing network performance, enhance wireless security, and improve the usefulness and value of important business applications. Location tracking provides enhanced visibility and control of air space, helping IT staff to deploy wireless networks that are as easy to manage and as effective to deploy as traditional wired networks.

To address lack-of-visibility problems, organizations need a cost-effective, easy-to-deploy solution for tracking and managing thousands of Wi-Fi devices and tags across a variety of business environments.

In heterogeneous environments, e.g. inside a building, though, the received power is a very complex function of distance, wall geometry, building infrastructures and obstacles. Even if you have a detailed model of the building, it takes a lengthy simulation to solve the direct problem of deriving signal strength given the location. This is what has motivated us to consider flexible models based on functions networks (neural networks) to implement a system to locate MSs.

The received signal strength (RSS), a measure of the power received by the client from an access point (AP), is the key parameter for establishing the position of a MS in an indoor environment. Traditionally, WLANs have used different measurement techniques to derive the position of MSs (Kaemarungsi, 2005; Raniwala & Chiueh, 2002). There are three major categories: closest access point-based techniques, location pattern or fingerprint and distance or angle measurement (see Fig. 1).

The *closest AP method* finds devices within the total coverage area of a single AP. It is the simplest but least accurate way to locate a device or user. With the closest AP method, the location tracking system identifies only devices within the total coverage

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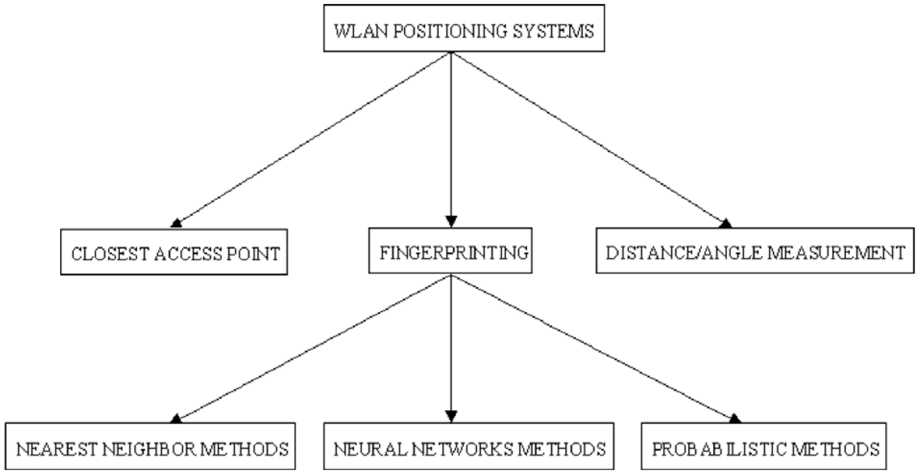

Fig. 1. WLAN positioning techniques.

area of a single AP. This area can be quite large and include multiple rooms. This system considers an AP to which a terminal connects as the user location.

The main distance measurement-based approach is known as *TDOA* (*Time* Difference of Arrival). This technique relies on the timing precision between the signal transmitter and receiver. It uses the propagation delay to calculate the distance between transmitter and receiver (Golden & Bateman, 2007). Therefore, a precise synchronization is very important in such systems. By combining at least three distances from three reference positions, triangulation can be used to estimate the MS's location. Such techniques will require a high accuracy clock in the communication system.

Angle of arrival (*AOA*) is a technique based on angle measurement. This methodology locates the MS by determining the signal angle of incidence. The location can be estimated using simple geometric relationships, like triangulation (Sanchez, Afonso, Macias, & Suarez, 2006).

In indoor environments, however, the distance between transmitter and receiver is usually shorter than the time resolution that the system can measure. Additionally, the MS is surrounded by scattered objects, which results in multiple angles of signal reception. Therefore, the *AOA* and *TDOA* approaches are difficult to implement in indoor environments.

Fingerprinting techniques generally only require measurement of received signal strength or other non-geometric features at several locations to form a database of location fingerprints (Kaemarungsi, 2006; Widyawan, Klepal, & Pesch, 2007). To estimate the mobile location, the system needs to first measure the received signal strength at particular locations and then search for the pattern or fingerprints with the closest match in the database.

Generally, the deployment of fingerprinting-based positioning systems can be divided into two phases. First, the location fingerprints are collected in the off-line or calibration phase by performing a site survey of the received signal strength (RSS) from multiple APs. Enough RSS measurements are taken to set up a database or a table of RSS patterns for predetermined points of the coverage area. The database of RSS patterns with their respective locations is called a *radio map*.

Second, a MS will report a sample measured vector of RSSs from different APs to a central server (or a group of APs will collect the RSS measurements from a MS and send it to the server) in the on-line or estimation phase. The server uses a positioning algorithm to estimate the location of the MS based on the radio map and reports the estimate back to the MS (or the application requesting the position information).

At this point we have several possibilities. The most common algorithm used to estimate the location computes the Euclidean distance between the sample measured RSS vector and each fingerprint in the database. For indoor positioning systems, other advanced algorithms and techniques, such as neural networks (Battiti, Le Nhat, & Villani, 2002; Debono & Buhagiar, 2004; Yiming, Biaz, Pandey, & Agrawal, 2006; Youssef & Agrawala, 2005), probabilistic methods (Chai & Yang, 2007; Kontkanen et al., 2004; Pan, Kwok, Yang, & Chen, 2006; Robinson & Psaromiligkos, 2005; Seigo & Kawaguchi, 2005) or fuzzy logic (Astrain, Villadangos, Garitagoitia, González-Mendivil, & Cholvim, 2006), have been introduced to determine the relationship between RSS samples and the location fingerprint in the radio map.

Other approaches have been presented. For example, some authors have proposed simulating the calibration phase with a ray-tracing model (Nezafat, Kaveh, Tsuji, & Fukagawa, 2004; Nuño & Páez-Borrallo, 2006; Zhong, Bin-Hong, Hao-Xing, Hsing-Yi, & Sarkar, 2001). However, this model requires a highly detailed model of the building. It could be tricky, if not unfeasible, to get such a detailed model. One of the main drawbacks of both of these models is that signal strength prediction is dependent not just on building layout, but also on the position of many other hard-to-model components, such as furniture, equipment and human beings.

So far, fingerprinting techniques with a real calibration phase have attracted more attention because they are a simple and the most effective solution for indoor environments.

Of the solutions that use RSSI to locate a mobile user, some scan the radioelectric spectrum of every square metre of the coverage area. Additionally, they only use one card brand. It is unfeasible to position another mobile user with a different Wi-Fi receiver using this solution.

The solution proposed here is a fingerprint-based positioning system that gets significantly better results than other similar systems because it normalizes measurements and optimizes clusters formed according to the physical features of the ground plan. In this way, the proposed solution is valid for any Wi-Fi receiver, as we account for the relative effect of walls and obstacles as a relative power increase or decrease.

Additionally, our technique does not require an exhaustive scan of the coverage area. Actually we present the results of sampling just one point per location. Our system can adapt to the geometry of each scenario and operate with any Wi-Fi device (irrespective of the manufacturer).

Finally, we present the results of implementing our system in practice and the evaluation tests run in a School of Computing